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Key Points:
- Common and event-specific driving factors of flood damage are identified from six major flood events in Germany
- Different types of inland water flooding are distinguished to investigate the impact of varying flood characteristics
- Bayesian Networks and Markov Blankets are learned from empirical data to understand flood-damaging processes

Supporting Information:
- Supporting Information S1

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Identifying Driving Factors in Flood-Damaging Processes Using Graphical Models

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Abstract Flood damage estimation is a core task in flood risk assessments and requires reliable flood loss models. Identifying the driving factors of flood loss at residential buildings and gaining insight into their relations is important to improve our understanding of flood damage processes. For that purpose, we learn probabilistic graphical models, which capture and illustrate (in-)dependencies between the considered variables. The models are learned based on postevent surveys with flood-affected residents after six flood events, which occurred in Germany between 2002 and 2013. Besides the sustained building damage, the survey data contain information about flooding parameters, early warning and emergency measures, property-level mitigation measures and preparedness, socioeconomic characteristics of the household, and building characteristics. The analysis considers the entire data set with a total of 4,468 cases as well as subsets of the data set partitioned into single flood events and flood types: river floods, levee breaches, surface water flooding, and groundwater floods, to reveal differences in the damaging processes. The learned networks suggest that the flood loss ratio of residential buildings is directly influenced by hydrological and hydraulic aspects as well as by building characteristics and property-level mitigation measures. The study demonstrates also that for different flood events and process types the building damage is influenced by varying factors. This suggests that flood damage models need to be capable of reproducing these differences for spatial and temporal model transfers.

1. Introduction

Floods are recurring natural hazards that may cause immense economic losses, especially in urban areas where assets are accumulated. In the last decades, flood damage has increased due to changes in socioeconomic wealth and urbanization (Barredo, 2009; Gerl et al., 2014; Kron et al., 2012). In this light, the development of reliable flood damage models is of great importance for loss estimation and risk assessment, as, for instance, required by the insurance industry to price risks and calculate premiums to assess their solvency or needed for the appraisal of flood mitigation measures in terms of cost-benefit ratios (Gerl et al., 2016; Merz et al., 2013; Thieken et al., 2005). Flood-damaging processes are complex, since they are influenced by the interaction of various factors, such as hydrological, hydraulic and building characteristics, as well as private precautionary measures, flood warning, and socioeconomic factors (Gerl et al., 2016; Kelman & Spence, 2004; Kreibich & Thieken, 2009; Merz et al., 2004; Schröter et al., 2014; Thieken et al., 2005), which need to be considered in flood damage models. In contrast, the established approach to flood loss estimation, dating back to the 1960s (Kates, 1968; White, 1945), is based on stage damage functions, which relate flood intensity metrics, most commonly the inundation depth, to the degree of damage. While this approach is appealing due to its simplicity and sparse data requirements, the outcomes of these models are associated with large uncertainty and hardly explain the variability of observed losses (Merz et al., 2004). Substantial improvements to the field have been achieved by expanding our knowledge about flood-influencing factors and their interactions based on empirical flood damage data sets (Merz et al., 2013; Thieken et al., 2005). Both the reduction of prediction uncertainty and the improvement of the reliability of flood damage models require additional efforts to advance the understanding of damaging processes and to deepen its theoretical foundations (Bubeck & Kreibich, 2011).

The development of multivariable models is an important contribution to this aim and has been brought forward during the last decade: Thieken et al. (2008) developed the rule-based multivariable Flood Loss Estimation Model for the private sector (FLEMOps). In this model, in addition to the water depth, the building type and the quality of the affected buildings are included. The model FLEMOps+, a model extension, considers additionally the contamination of water and precautionary measures (Thieken et al., 2008). Elmer et al. (2010) also integrated the flood frequency into the loss model and hence further improved its performance. Merz et al. (2013) and Schröter et al. (2014) extended the set of variables included in flood loss models across a range of influencing characteristics including inundation duration and building characteristics, early warning and precaution as well as socioeconomic factors considering tree-based methods and Bayesian Networks (BNs) for flood damage modeling. Vogel et al. (2012) proposed a BN model approach, which is based on a probabilistic formalism for analyzing the influence of the considered variables on flood damage to residential buildings. In these studies flood damage models were developed based on empirical data, which were retrieved from computer-aided telephone interviews conducted with flood-affected households after major floods that occurred in Germany between 2002 and 2006.

In this paper we intend to further improve the insight into flood-damaging processes by identifying the most relevant dependency relations between the considered variables. Compared to Vogel et al. (2012), Merz et al. (2013), and Schröter et al. (2014), the used data base was extended considerably, including additional computer-aided telephone interviews with another 2,310 households affected by floods in 2010, 2011, and 2013 in different parts of Germany, resulting in one of the most comprehensive data sets on residential flood impacts on the microscale worldwide.

Further, we address the transferability of damage functions in time and space, which is often an implicit assumption in damage modeling. In theory, multivariable models provide the flexibility to capture large variations of event characteristics. Yet the development of reliable transferable damage models requires large and heterogeneous data sets (Wagenaar et al., 2018). In practice, the prediction quality still seems to be limited, if damage models are transferred across events and regions (e.g., Cammerer et al., 2013; Schröter et al., 2014; Wagenaar et al., 2018). Besides changes in exposure and vulnerability, this might be due to differences in the flooding process. There is indication that different flood types result in different amounts and types of (structural) damage (see Kreibich & Thieken, 2008 for groundwater floods and Laudan et al., 2017 for flash floods). By including the flood type as predictor variable, we aim to analyze the need to distinguish damage models for different flood types. Furthermore, we include the event year and the federal state in which the affected household is located to serve as proxies for regional peculiarities, flood management structures, or other prevailing circumstances. Thus, severe floods as the ones of 2002 and 2013 might cause a demand surge resulting in increased construction prices due to shortages of renovation capacity and consequently challenge the transferability of loss models across time and space. We expect that event year and federal state show a strong relation to the flood damage. This would point to the need for a better understanding of regional and event characteristics to allow for a successful flood damage model transfer. With this in mind, we also consider the different flood types and flood events individually.

Additionally, we include the existence of a flood insurance as additional variable in the data set. There is evidence that insured households do get higher and quicker loss compensation than uninsured households, who have to bear the damage from their own resources or—in some cases—from governmental payouts (Thieken et al., 2006; Thieken, 2018). The consideration of flood insurance allows us to explore whether differences in compensation do include moral hazard that could be reflected by higher losses of insured households or insurance is part of a more comprehensive risk-reducing strategy (Thieken, 2018).

Applying novel data-driven probabilistic graphical modeling approaches, that is, BNs and Markov Blankets (MBs), we aim to identify the variables that control the flood damage caused to residential buildings in the first instance. Since a good predictability of BNs in the context of flood damage models has already been indicated by Vogel et al. (2013) and Schröter et al. (2014), the current paper focuses on the identification of the most important factors that drive flood damage, especially with regard to different flood types and distinguishing between individual flood events.

After describing the considered flood events and the employed data set in sections 2.1 and 2.2, we give an introduction into the applied graphical models: BNs in section 2.3 and MBs in section 2.4. In section 3 we present the BN learned from the entire data set (section 3.1) and the MBs of the flood loss ratio (section 3.2) learned from the entire data set as well as data subsets for individual events and types of flooding. The resulting graphical models are compared with each other in section 4.1. Further, the results are compared with previous studies and linked to the characteristics of the considered flood events in section 4.2. Section

Table 1
Brief Characterization of the Six Flood Events in Germany

Flood event	Preconditions and triggering meteorological events	Affected river basin and hydrologic severity S[a]	Damage in EUR
August 2002	High preceding soil moisture was followed by a Vb weather system with record-breaking rainfall on 12/13 August in the Alps and the middle hills, particularly in Saxon Ore Mountains (Erzgebirge)	Danube, Elbe (S = 35.4)	$11,600 \times 10^6$ (Thieken et al., 2006)
August 2005	Reduced snow cover formation due to mild temperatures in the Alpine region and high soil moisture were followed by a Vb weather system with extensive rainfall in the Western Alps	Danube, Elbe (S = 19.3)	175×10^6 (Kron, 2009)
March/April 2006	Complete and quick snowmelt in the middle hills due to a rapid temperature increase, accompanied by heavy rainfall from westerly cyclones	Danube, Elbe (S = 17.3)	120×10^6 (Kron & Ellenrieder, 2008)
August/September 2010	Three consecutive fronts with heavy rainfall; pluvial floods in the northwest of Germany, for example, in the city of Osnabrück; flooding was intensified by a dam breach at the Witka River in the Oder/Odra catchment;	Elbe, Oder/Odra, Ems (S not specified)	839×10^6 (EC-European Commission, 2014)
January 2011	Spacious snowmelt in the middle hills due to rapid temperature increase and heavy rainfall followed by more intense rainfall	Rhine, Danube, Elbe, Oder/Odra, Weser (S not specified)	120×10^6 (*Munich Re NatCatSERVICE*)
May/ June 2013	A very wet May resulted in very high saturated soils on which high rainfall amounts were dumped at the end of May	Rhine, Danube, Elbe, Weser(S = 74.9)	Up to $8,000 \times 10^6$ (Thieken, Bessel, et al., 2016)

[a] *S* is the severity of the flood event for all of Germany. It reflects the share of river reaches in which the flood discharge exceeded the 5-year discharge ($Q >$ HQ5); see Schröter et al. (2015) for details.

4.3 discusses the transferability assumption of flood damage models with regard to multivariable models. Conclusions are summarized in section 5.

2. Data and Method

2.1. Event Description

The studied data comprise six flood events, which are characterized by different mechanisms in their formation and development. The events in spring 2006 and January 2011 were typical slow-onset floods that are characterized by a rain-on-snow-mechanism, that is, after a winterly period with high amounts of snow stored in the catchments, warm westerly cyclones caused massive snowmelt. Overland flow was intensified by additional rainfall and frozen soils that suppressed infiltration. In contrast, all other events were summer floods which were triggered by atmospheric circulations that carried warm moist air masses from the Mediterranean Sea or Eastern Europe to Central Europe (see Kienzler et al., 2015, for brief event descriptions). Except for the flood in 2013, these summer floods were also characterized by heavy, partly record-breaking (in August 2002) rainfall resulting in surface water flooding and flash floods in many places within the affected catchments (see Table 1). In June 2013, widespread flooding occurred due to high antecedent soil moisture in most of Germany and high rainfall amounts (Schröter et al., 2015). From a hydrological point of view, this resulted in the most severe flood in Germany over the past 60 years (Merz et al., 2014), which is indicated by the high *S* value of 75 in Table 1. However, due to a betterment of flood risk management and the different flood dynamic, the overall damage was with approximately EUR 8 billion much lower than in 2002 (Thieken, Bessel, et al., 2016; Thieken, Kienzler, et al., 2016). Table 1 also reveals that the four flood events between 2005 and 2011 caused considerably less damage.

2.2. Data Description

After Germany was hit by a major flood in 2002 that caused an unprecedented amount of damage, in total EUR 11.6 billion (as of 2005), efforts to collect loss data and information about factors that determine the type and amount of flood damage were substantially increased. Since then, flood-affected residents have been surveyed by computer-aided telephone interviews in the aftermath of six flood events, that is, after riverine floods in 2002, 2005, 2006, 2010, 2011, and 2013 using a standardized questionnaire (Kienzler et al., 2015; Thieken et al., 2005, 2007; Thieken, Bessel, et al., 2016).

For the loss data collection, it was aimed to investigate representative random samples of all damaged households per event. Therefore, lists of inundated streets and zip codes were compiled. For the survey after the 2002 flood, these lists were generated from information provided by affected communities and districts upon request. In successive surveys, the lists were compiled from flood reports or press releases as well as with the help of flood masks derived from satellite images (DLR, Centre for Satellite-Based Crisis Information, www.zki.dlr.de) that were intersected with street maps (Thieken et al., 2017).

The street lists served as a basis to retrieve telephone numbers of potentially affected residents from the public telephone directory. This was done by the subcontracted pollster (SOKO GmbH, Bielefeld or explorare market research institute GmbH, Bielefeld), and so was the sampling. For the household survey of the 2002 flood, a building specific random sample of households was generated distinguishing three regions with different hydrological and socioeconomic conditions: (1) Bavaria, (2) the Saxon Ore Mountains, (3) communities along the rivers Mulde and Elbe in Saxony and Saxony-Anhalt (Thieken et al., 2007). A similar sampling was applied in the survey of the 2013 flood (DKKV- Deutsches Komitee Katastrophenvorsorge, 2015). Since the floods between 2002 and 2013 were less severe in terms of hydrological load and damage (see Table 1), the corresponding surveys included all retrieved telephone numbers. However, since approximately 40% of the called households reported that they had not been affected by the flood, it was difficult to achieve a sufficient number of interviews (Kienzler et al., 2015). Therefore, the resulting data sets are much smaller for these events (see Table 2). In total, 4,468 interviews were undertaken for all six events, whereby 75% of the data are related to the major floods of 2002 or 2013.

During the survey the person in the household with the best knowledge about the flood event was questioned for 30 min on average. The questionnaire covered a wide range of topics that potentially influence flood damage at residential properties (Thieken et al., 2005; 2017), that is,

1. Characteristics of the flood: water depth, flood duration, flow velocity, type of flooding (e.g., sudden groundwater rise, surface water flooding or overflow of the sewer system, river inundation, levee breaches), contamination of the flood water;
2. Flood warning: receipt and sources of flood alerts, information content of the warning message, lead time;
3. (Short-term) emergency measures: kind of undertaken emergency measures and perceived effectiveness, number of people involved in emergency measures, time spent on emergency measures;
4. Characteristics of the affected building: for example, building type, construction material, number of stories, total living area, type and utilization of the basement;
5. (Long-term) precautionary measures (property-level mitigation measures): type of measure, time of implementation (i.e., before or after the flood), perceived effectiveness of self-protective measures;
6. Flood experience: number of previously experienced events, date of most recent flood, date of the most severe event, knowledge about living in a flood-prone area;
7. Loss: repair costs (building) and replacement costs (household contents);
8. Further topics: evacuation, cleanup work and recovery, aid and financial compensation, sociodemographic information.

Altogether, the questionnaire comprised about 180 questions. For most of them, lists with possible answers were provided resulting in a highly standardized data set suitable for quantitative research and data analysis. Some parts of the questionnaire were filtered. For example, in general only homeowners were asked about the damage to the building, because it was assumed that most tenants could not answer the technical questions.

Table 2
Overview of the Surveys Among Residents in Germany Affected by Flooding Between 2002 and 2013 (Extended From Kienzler et al., 2015)

Flood event	Data collection campaign	Survey period (field time)	Time lag between flood event and the survey (month)	Original sample size n_{org}	Cleaned sample size[a] n
August 2002	DFNK	8 April to 10 June 2003	8–10	1,697	947
August 2005	MEDIS	20 November to 21 December 2006	15–16	305	127
April 2006	MEDIS	20 November to 21 December 2006	7–8	156	61
August 2010	Joint venture	16 February to 20 March 2012	18–19	440	242
January 2011	Joint venture	16 February to 20 March 2012	13–14	218	103
June 2013	Flood 2013	18 February to 24 March 2014	8–9	1,652	803
Total				4,468	2,283

[a]The cleaned sample size contains only cases for which the building loss ratio is available.

Therefore, the cleaned sample size contains only 2,283 out of the original 4,468 cases, that is, 51% (Table 2). These are cases for which a building loss ratio, that is, the financial loss at the affected buildings in relation to the overall asset value of that building was available. It cannot be ruled out that the data filtering introduces a bias, yet we consider it to be of minor importance for the detection of damage influencing variables. We rather believe that keeping the data with unknown flood loss ratio would blur the dependencies to the flood loss ratio and hamper their detection.

After its first use in the aftermath of the 2002-flood, the questionnaire has been slightly revised for the consecutive campaigns. However, for this analysis only items were used that were questioned in all campaigns or summarizing indicators, which were introduced by Thieken et al. (2005) (e.g., for emergency measures, precaution, flood experience, or socioeconomic status) and could be derived for all campaigns. It should be noted, however, that for the 2002 data set the method, how the dominating flood type was assigned, differed from the consecutive surveys. In 2002, flood types were assigned by combining the survey data with external data on levee breaches as well as on maps of flood dynamics to distinguish cases with riverine flood and surface water flooding. Groundwater floods were assigned to cases in which people reported that the water entered the building from below. Then the average loss ratio was determined per flood type, revealing that levee breaches caused the highest losses, followed by riverine floods and surface water flooding; groundwater floods caused only minor losses (Cammerer & Thieken, 2011). This order of severity was used in later surveys to assign a dominating flood type to cases, in which multiple answers had been given to the (newly introduced) question about the source of the flooding. As a consequence, riverine flooding was assigned in most cases that reported mixed flood types.

All considered items and indicators are listed in Table 3 together with their scales, units, value ranges, and percentages of missing values. It reveals that for some items the share of missing data amounts up to almost 30%. Besides the monthly net income, to which answering is regularly refused, this holds for items that were filtered in the questionnaire. For example, only residents that undertook emergency measures and had been warned were subsequently asked about the time gap between the flood alert and the implementation of emergency measures. Consequently, the share of missing data amounted to 25%. Similarly, only residents that had been officially warned were asked whether they knew (on the basis of the provided warning information) how to protect themselves and their property from damage. It was only in the survey of the 2013 flood that all residents were asked a similar question. Removing incomplete data records from the set of data, as typically done for applications of state-of-the-art methods, would considerably reduce the size of the data set as well as the amount of information contained in the data. Graphical models allow to take incomplete records into account, even though learning graphical models from incomplete data sets is challenging (see section 2.3).

In what follows it will be outlined how graphical models were applied to the cleaned data set with 2,283 cases as well as to data subsets for each of the six flood events or each of four flood types: riverine floods, surface water flooding, levee breaches, and groundwater floods (number of cases are included in Table 3). To allow a comparison of the outcomes with these innovative methods with commonly applied methods and former analyses, we also applied a correlation analysis (Spearman) and a principal component analysis (PCA) with varimax rotation, analog to Thieken et al. (2005). For this, the nominal items, for example, the flood type, were omitted or coded in a way that can be interpreted as an order. The results of the correlation analysis and PCA are presented in the supporting information to this paper.

Table 3
Items of the Questionnaire Used in This Study and Their Characteristics

Item	MS[a]	Units or categories[b]	Data range and median[c] (M)	Missing[d] (%)
Characteristics of the flood event				
Water depth	C	cm above ground surface	−248 … 890; M = 50	2.2
Inundation duration	C	hours	1 … 1440; M = 72	3.5
Flow velocity indicator	O	Assessed on a rank scale: 0 (no flow) to 6 (very high velocity)	0 … 6; M = 3	10.1
Contamination of the flood water	O	0 (no contamination) to 2 (heavy contamination, e.g., by oil)	0 … 2; M = 0	0.7
Flood type	N	levee breach (516); river flood (1,192); surface water flood (250); groundwater flood (308)		0.7
Federal state	N	SH: Schleswig-Holstein (5); NI: Lower-Saxony (81); NW: North Rhine-Westphalia (3); HE: Hesse (2); RP: Rhineland-Palatinate (31); BW: Baden-Wurttemberg (29); BY: Bavaria (580); BB: Brandenburg (3); MV: Mecklenburg Western Pomerania (2); SN: Saxony (994); ST: Saxony-Anhalt (458); TH: Thuringia (95)		0.0
Year of the event	N	2002 (947); 2005 (127); 2006 (61); 2010 (242); 2011 (103); 2013 (803)		0.0
Warning and response before/during the flood event (temporal resistance)				
Early warning lead time	C	hours	0 … 336; M = 50	2.2
Perceived knowledge about self protection (Quality of warning)	O	Rank scale from 1 (I knew exactly what to do) to 6 (I had no idea what to do)	1 … 6; M = 2	29.5
Indicator for the source of the warning	O	Rank scale from 0 (no warning) to 4 (official alert by authorities); see Thieken et al. (2005)	0 … 4; M = 3	0.7
Indicator for the content of the warning information	O	Rank scale from 0 (no helpful information) to 16 (many helpful pieces of information); see Thieken et al. (2005)	0 … 16; M = 2	5.9
Time elapsed between alert and implementation of emergency measures	C	hours	0 … 234; M = 0	25.1
Indicator for emergency measures	O	Rank scale from 0 (no measures performed) to 17 (many measures performed effectively); see Thieken et al. (2005)	0 … 17; M = 7	0.0

Table 3 (*continued*)

Item	MS[a]	Units or categories[b]	Data range and median[c] (M)	Missing[d] (%)
Property-level mitigation measures and risk awareness (permanent resistance)				
(Classified) indicator for property-level mitigation measures (precaution)	O	Rank scale from 0 (no measures performed before the flood) to 2 (very good precaution) as used in FLEMO	0 … 2; M = 1	0.0
Perceived efficiency of private mitigation	O	Rank scale from 1 (private mitigation can reduce damage very efficiently) to 6 (private mitigation cannot reduce damage at all)	1 … 6; M = 3	3.7
(Classified) indicator for previous flood experience	O	0 (no previously experienced floods) to 4 (recently experienced flood damage); see Thieken et al. (2005)	0 … 4; M = 0	3.0
Knowledge about the flood hazard of the residence	N	no knowledge (674); knowledge of flood hazard or previously experienced flood (1,580)		1.3
Flood insurance	N	no flood insurance (1,130); flood insurance at the time of the event (1,131)		1.0
Characteristics of the damaged building				
Building type	N	multifamily home (471); semidetached / terraced house (460); detached one-family home (1,350)		0.1
Homeownership	N	tenant (75); owner of a flat (55); homeowner (2,153)		0.0
Number of flats in the building	C	Number of flats	1 … 45; M = 1	2.0
Floor space of the building	C	m^2	20 … 2100; M = 130	17.5
Perceived quality of the building	O	Rank scale from 1 (very good quality) to 6 (very bad quality)	1 … 6; M = 2	0.5

2.3. Bayesian Networks

The applied approaches, BNs and MBs, combine elements from probability theory with graph theory. Treating all model components as random variables, they enable a direct consideration of uncertainties. BNs aim to model the joint probability distribution of all considered variables by translating dependencies and independencies between the variables into a graph structure. Considering all variables simultaneously, BNs provide a better understanding of the system under study than pairwise investigations. The multivariate approach allows us to consider the joint effects of several impact factors and to model complex and nonlinear interactions between the considered variables. A graphical network representation provides an intuitive insight into the dependency relations between the model components. Since the early 1990s BNs became increasingly popular for modeling complex processes in environmental sciences (Aguilera et al., 2011; Cain, 2001; Molina & Zazo, 2018; Newton, 2009).

2.3.1. Definition and Notation

A BN depicts all random variables of the model as nodes in a network with directed edges that encode the dependency relations between the variables. Due to modeling constraints the network has to form a directed

Table 3 (*continued*)

Building value	C	Euro (in prices of 2013)	98 496 … 10 379 533; M = 421 200	0.1
Socioeconomic variables				
Age of the interviewee	C	Years	16 … 99; M = 55	3.4
Household size	C	Number of people	1 … 20; M = 2	2.0
Children per household	C	Number of children	0 … 6; M = 0	3.0
Elderly people per household	C	Number of elderly people	0 … 6; M = 0	2.8
Classified monthly net income of the household	O	Classes from 11 (> 500 Euro) to 16 (3,000 Euro and more)	11 … 16; M = 14	25.3
Socioeconomic status according to Plapp (2003)	O	1: lower class; 2: lower middle class; 3: upper middle class; 4: upper class	1 … 4; M = 3	25.4
Adverse effects				
Loss ratio (building)	C	0: no damage, 1: total loss	0 … 1; M = 0.05	0.0

[a]Scale of the measurement with C = continuous data; O = ordinal data; N = nominal data. [b]Units or categories. For nominal items the absolute number per category is given in braces: (*n*). [c]Data range and median (M) considering the 2283 cases of the cleaned data set. [d]Percentage of missing observations in the cleaned data set.

acyclic graph (DAG). That means, following a path of edges in the direction of their orientation, a node must not be passed twice (no cycles). Figure 1 shows a BN example that illustrates the influencing factors on the flood loss of buildings based on the scheme presented by Thieken et al. (2005). The graphical representation of the model structure permits an intuitive insight into complex systems and the modeled dependency relations and thus offers a new opportunity for communication in academia and to decision makers.

Nodes that point to a node X_i are called parents, $\mathbf{X}_{\mathrm{Pa}(i)}$, of X_i. Consequently, nodes that X_i points at are called children of X_i. In a causal network parents and children correspond to causes and effects. Aside from the DAG, the definition of a BN requires parameters, $\boldsymbol{\theta}$, that define the local probability distribution for each variable conditioned on its parents: $P(X_i|\mathbf{X}_{\mathrm{Pa}(i)})$. According to the rules of probability theory, the joint probability distribution of all variables decomposes into the product of their local probabilities

$$P(X_1, \dots, X_k) = \prod_{i=1}^{k} P(X_i|\mathbf{X}_{\mathrm{Pa}(i)}).$$

Consequently, each probability of interest can be inferred from the local probabilities provided by the BN definition. Therefore, graphical models are very flexible and can be used to study specific case scenarios and courses of actions. Additionally, the probabilistic nature of BNs allows for an explicit treatment of uncertainty. In contrast to models that capture expected values only, that is, deterministic models, BNs contain additional information, for example, about exceedance probabilities of certain threshold values. They consequently pose a valuable tool for decision support. For example, considering the BN in Figure 1, we could assume a specific hydrological load and calculate the corresponding probabilities for the building's flood loss. This could be done even if the permanent resistance, which has according to the graph structure an effect on the building loss, is unknown. For the purpose of decision support, we could further study the effect of different settings for temporal resistance on the building loss. We refer to basic literature (Jensen & Nielsen, 2007; Koller & Friedman, 2009) for a detailed introduction into BNs.

2.3.2. Learning Bayesian Networks From Data

The graphical representation of BNs facilitates expert and stakeholder involvement in the modeling process. Expert knowledge about dependency relations can be respected by modifying edges accordingly. Thus, the DAG could be defined completely based on expert knowledge. Yet in contrast to many state-of-the-art approaches (e.g., regression models, such as stage damage functions for flood damage modeling) BNs do not require any assumptions about the functional form of the model. If the system under study is not well understood, the DAG as well as the set of parameters, $\boldsymbol{\theta}$, can be determined completely data driven.

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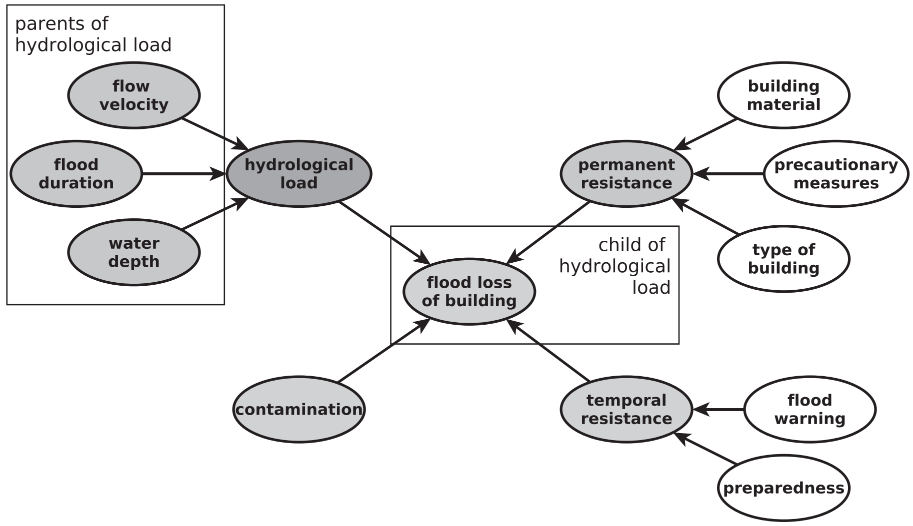

Figure 1. A Bayesian Network example that illustrates influencing factors on the flood loss of buildings, based on the scheme presented by Thieken et al. (2005). Nodes that point at a node of interest, for example, hydrological load (dark gray node), are called parents of that node. Nodes that are pointed at are called children of the pointing node. All variables that provide direct information for predicting the node of interest (light gray nodes) form the Markov Blanket of the corresponding node (see section 2.4).

Algorithms for learning BNs from data can be divided into two basic concepts (Koller & Friedman, 2009). *Constraint-based* algorithms construct the DAG based on conditional independence tests and aim to find a network that matches the detected independencies of the considered data set best. Variations of the algorithm exist due to different choices of independence tests, as well as different ways of transforming the test results into a DAG. *Score-based* algorithms search in the space of DAGs for high scoring models. The score is an expression of how well the considered model fits the observed data. Variations of the algorithm emerge from different choices for the search algorithm and scoring function (Riggelsen, 2006a). Several software tools and packages provide out-of-the-box functionalities for both types of algorithms (Madsen et al., 2003; Scutari & Denis, 2014; Uusitalo, 2007). Yet the settings for both types of algorithms must be chosen carefully, since they do not only affect the computational costs but may have significant impact on the results.

As mentioned in section 2.2 the data at hand contain several incomplete data records, as a result of the survey design and item nonresponses of participants (see Table 3). Removing the incomplete data records would diminish the information content of the data considerably. On top comes the hybrid nature of the data set, which means that discrete variables are mixed with continuous variables. The family of distribution for the continuous variables is mostly unknown. Due to these constraints an application of standard software is not advantageous. Instead, we make use of an advanced score-based algorithm that was developed for incomplete, hybrid data sets (Vogel et al., 2014). The single challenges addressed by the algorithm are explained in the following, while Table 4 provides a summary of the applied approaches.

2.3.3. Learning Bayesian Networks From Incomplete Hybrid Data Sets

We use a hill climber search algorithm (Castelo & Kocka, 2003) to find the most probable BN—in other words the most probable combination of DAG and θ—for the observed data set, **d**. The corresponding BN MAP (maximum a posteriori) score: $P(\text{DAG}, \theta \mid \mathbf{d})$ follows the Bayesian approach (Riggelsen, 2008). Originally designed for discrete data, the score was extended by Vogel, et al. (2012) to work on hybrid data sets by searching for an optimal discretization of the continuous variables. Sticking to the Bayesian approach the extended BN MAP score: $P(\text{DAG}, \theta, \text{D} \mid \mathbf{d})$ aims to find the most probable combination of BN and discretization, D, given the observed data. Considering the discretization in context with the BN allows to respect the interactions between the variables in the discretization process. They are typically neglected, if the discretization is done prior to BN learning. The calculation of the (extended) MAP score requires a completely observed data set. To overcome this problem, missing values in the data set are estimated based on present observations by applying the *Markov Blanket predictor* (Riggelsen, 2006b; Vogel et al., 2013), which offers a reasonable trade-off between accuracy and computational costs.

Table 4
Summary of Challenges Emerging for Learning a BN From Flood Damage Survey Data and the Applied Approaches to Address These Challenges

Challenge	Approach	Reference
Learn BN from data(discrete and complete)	hill climber search algorithm; maximize BN MAP score: P(DAG , θ | **d**)	Riggelsen (2008)
Deal with hybrid data	iterative proceeding: • find optimal discretization: D • maximize extended BN MAP score: P(DAG , θ, D | **d**)	Vogel, et al. (2012)
Deal with incomplete data	estimate missing values by applying the Markov Blanket predictor	Riggelsen (2006b) and Vogel et al. (2013)

Especially for complex systems a huge data set is required to learn the (in-)dependencies between the considered variables reliably. The number of detected edges depends not only on the true dependency relations but also on the applied algorithm and the amount of available data records. Due to regularization constraints, learning BNs from few data records usually results in sparsely connected DAGs. A BN learned from a small or medium-sized data set might consequently fail to capture relevant dependency relations for a variable of primary interest (e.g., the flood loss).

2.4. Markov Blankets

In contrast to BNs, a MB does not aim to describe the complete system, but focuses on a specific target variable, X_i, and the variables that deliver direct information about that variable of interest. In other words a MB can be considered as the smallest subnetwork of a BN that contains all variables that are relevant for the prediction of X_i. Instead of modeling the joint probability distribution of all variables, MBs rather model the conditional distribution of the target variable. They consequently often do a better job in variable selection tasks than BNs. While BNs have already successfully been applied in natural hazard assessments (Blaser et al., 2011; Kühn et al., 2011; Straub, 2005; Vogel et al., 2014), we have no knowledge about direct applications of MBs in that field. Yet MBs are successfully applied for feature selection in several other scientific disciplines, for example, in the field of bioinformatics and microarrays (Dernoncourt et al., 2011; Saeys et al., 2007; Zhu et al., 2007) as well as for text classification (Javed et al., 2015).

2.4.1. Definition and Notation

The MB of X_i, which we denote by MB(X_i), is composed of its parents, its children, and the parents of its children. Despite our interest in the MB of *flood loss ratio*, we highlighted the MB of *hydrological load* in Figure 1 (light gray nodes) for the purpose of illustration, since the flood loss has no children or parents of children. It is obvious that the parents of hydrological load provide information about the variable itself. Similarly, we can infer knowledge about the hydrological load by observing the flood loss, for example, a high building loss increases our belief in a high hydrological load. The relation to *contamination*, *permanent resistance*, and *temporal resistance* is less obvious, since these variables are assumed to be independent of the hydrological load. Yet they become conditionally dependent, if the flood loss is known. While our belief in a high hydrological load increases for a high building loss, it will, for example, be adjusted downward, if we get the additional information about a very low temporal or permanent resistance of the building. For a detailed introduction into the concept of MBs we refer to basic literature (Pearl, 1988).

2.4.2. Learning Markov Blankets From Data

Usually *constraint-based* structure-learning algorithms are applied to learn MBs from data (Fu & Desmarais, 2010). These learning algorithms employ conditional independence tests to construct a BN in agreement with the test results. In the scope of this paper we apply independence tests based on the *mutual information* to learn the MB of the *loss ratio*. Mutual information is an entropy-based information theoretic measure that quantifies the amount of information that is shared between two variables (Singhal, 2007).

The “bnlearn” package in R provides several constraint-based algorithms for MB learning which apply mutual information. Those are in detail

Table 5
Summary of Challenges Emerging for Learning MBs From Flood Damage Survey Data and the Applied Approaches to Address These Challenges

Challenge	Approach	Reference
Learn MB from data(discrete and complete)	constrained-based algorithms applying mutual information: Grow-Shrink, (Fast / Interleaved) Incremental Association Markov Blanket	Margaritis (2003), Tsamardinos et al. (2003), and Yaramakala and Margaritis (2005)
Deal with hybrid data	discretization in data preprocessing, minimizing the class entropy	Fayyad and Irani (1993) and Vogel, Riggelsen, Merz, et al. (2012)
Deal with incomplete data	estimate missing values by applying the Markov Blanket predictor	Riggelsen (2006b) and Vogel et al. (2013)

1. Grow-Shrink (GS; Margaritis, 2003)
2. Incremental Association Markov Blanket (IAMB; Tsamardinos et al., 2003)
3. Interleaved Incremental Association Markov Blanket (Inter-IAMB; Tsamardinos et al., 2003)
4. Fast Incremental Association Markov Blanket (Fast-IAMB; Yaramakala & Margaritis, 2005).

The individual algorithms differ in their sequential arrangements of the conditional independence tests and the selections for the conditioning set of variables. For a detailed description of the single algorithms we refer to the above mentioned literature. Similarly to the BN learning, an out-of-the-box application at the flood damage survey data is not possible. We explain in the following, how we address the challenges of hybrid and incomplete data for MB learning and summarize the applied approaches in Table 5.

2.4.3. Learning Markov Blankets From Incomplete Hybrid Data Sets

For a straightforward application of the mentioned MB learning algorithms to the flood damage data, the data set needs to be discretized again. Since we do not use a score-based algorithm for the MB construction, the discretization approach used for BN learning is not applicable here. Instead, we use a multiinterval discretization approach for classification learning and discretize the data as preprocessing step by measuring the class entropy (Fayyad & Irani, 1993, Vogel, et al., 2012). The interval boundaries of a predictor are chosen such, that by dividing the data set at the chosen boundary, the entropy of the response variable in the resulting subsets is minimized. Consequently each variable is discretized in a way that is best suited to make predictions about the flood loss ratio. The chosen discretization may have a strong impact on the final network. While fine discretizations usually result in less dense networks (small Markov Blankets), a coarse discretization leads to a denser network (large Markov Blankets). Further, the position of the interval boundaries can affect the detected network structure. We consider the chosen discretization approach to be suitable for detecting relevant relations between the predictors and the loss ratio, since it was designed for that purpose.

Analog to the BN learning, the application of the MB learn algorithm requires a fully observed data set. Therefore, missing values in the data set are sampled from the conditional probability distributions provided by the Markov Blanket predictor, that is already applied in section 2.3. To account for random effects in the sampling, we run 50 iterations for each MB algorithm, each time renewing the sample of the missing values. The most frequently learned MBs are shown in section 3.2.

3. Results

This section provides the probabilistic graphical models, which were learned from the data recorded after the six major flood events between 2002 and 2013 in Germany. The first subsection (section 3.1) presents the BN that was learned based on the entire data set. The second subsection (section 3.2) shows the MBs of loss ratio derived from the entire data set as well as data subsets for the individual flood events and different types of flooding. The learned graph structures show, which variables share common information in the underlying data and which variables form closely related clusters. Further, being present in the MB of loss ratio indicates

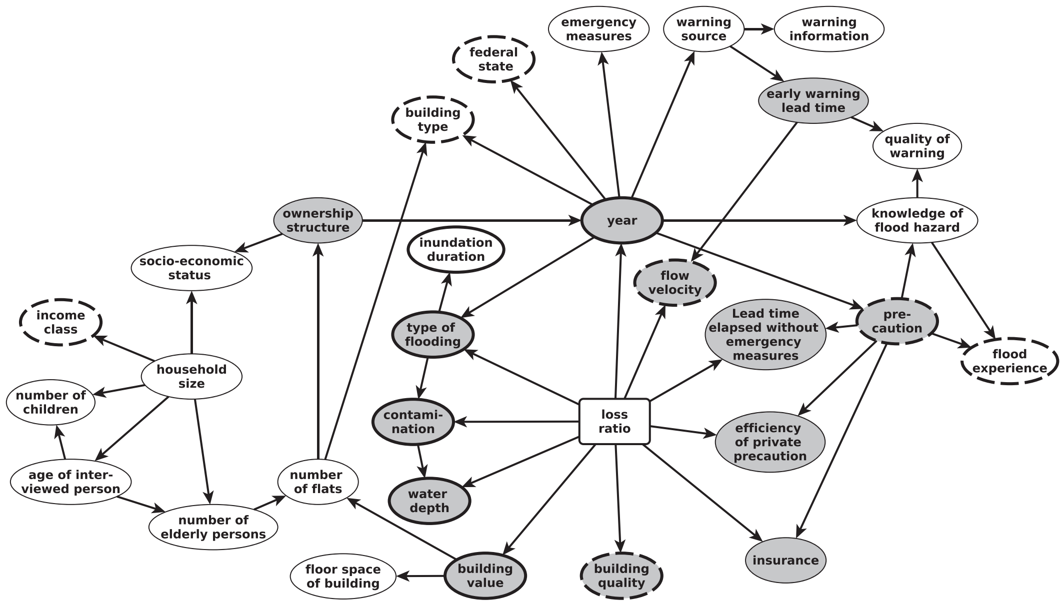

Figure 2. BN learned from the data set collected after flood events in Germany between 2002 and 2013 (n = 2,283). Variables that form the MB of the flood loss ratio in this BN are marked in gray. Variables that are detected by constraint-based MB learning are marked with a bold frame, if present in a MB learned from the entire data set or in a dashed bold framed, if only present in a MB learned from a data subset (see section 3.2).

which variables may serve best as predictors for the caused flood damage. For comparison, we also applied a correlation analysis and PCA on the entire data set. The results are provided in the supporting information.

3.1. Bayesian Networks

Figure 2 shows a BN that was learned from the data set described in section 2.2. We like to stress that the shown BN is not a unique solution. Even though the applied Hill-Climber Monte Carlo search algorithm was shown to result in the global maximum, if the underlying data set is infinite (Castelo & Kocka, 2003), random processes in the search algorithm generally lead to different outputs, if the algorithm is applied several times to the same finite data set. Consequently, slight changes in the MB of the flood loss ratio as well as the entire DAG are possible in repeated applications. Yet the most dominant dependency relations will be captured in all search results.

Investigating the MB of the flood loss ratio (marked in gray in Figure 2), it can be seen that besides inundation duration, all factors characterizing the hydrological load, that is, water depth, type of flooding, flow velocity, and contamination, are directly linked to the loss ratio. This indicates a high explanatory power of these variables. Further, variables characterizing the building resistance, both permanently (building value, building quality, efficiency of private precaution) and temporally (lead time elapsed without emergency measures), are directly linked to loss ratio. Socioeconomic and warning-related factors seem to be of less importance.

3.2. Markov Blankets

To get a better understanding of the role of the individual factors, we investigate the individual events and different flood types separately. Since the available data sets for the single events are comparatively small, we consider MBs of the loss ratio instead of BNs for that purpose. As mentioned in section 2.4, MBs often do a better job in detecting the variables with direct impact on the target variable, especially if the size of underlying data set is small. For completeness and comparability to the learned BN, we also derive the MB of the loss ratio from the entire data set.

We are aware that a mere counting of a variable's occurrence in the detected MBs does not precisely reflect its importance. Which variables are included in the Markov Blanket depends to a certain extent on the applied algorithm and the quality of the considered underlying data set (e.g., amount of data). Yet we expect variables with a strong impact on the flood loss ratio to be detected in (almost) all cases, while other variables with a weaker impact are only detected in some cases. The detected MBs give some indication and serve as basis for a comparison with existing models (see section 4.2).

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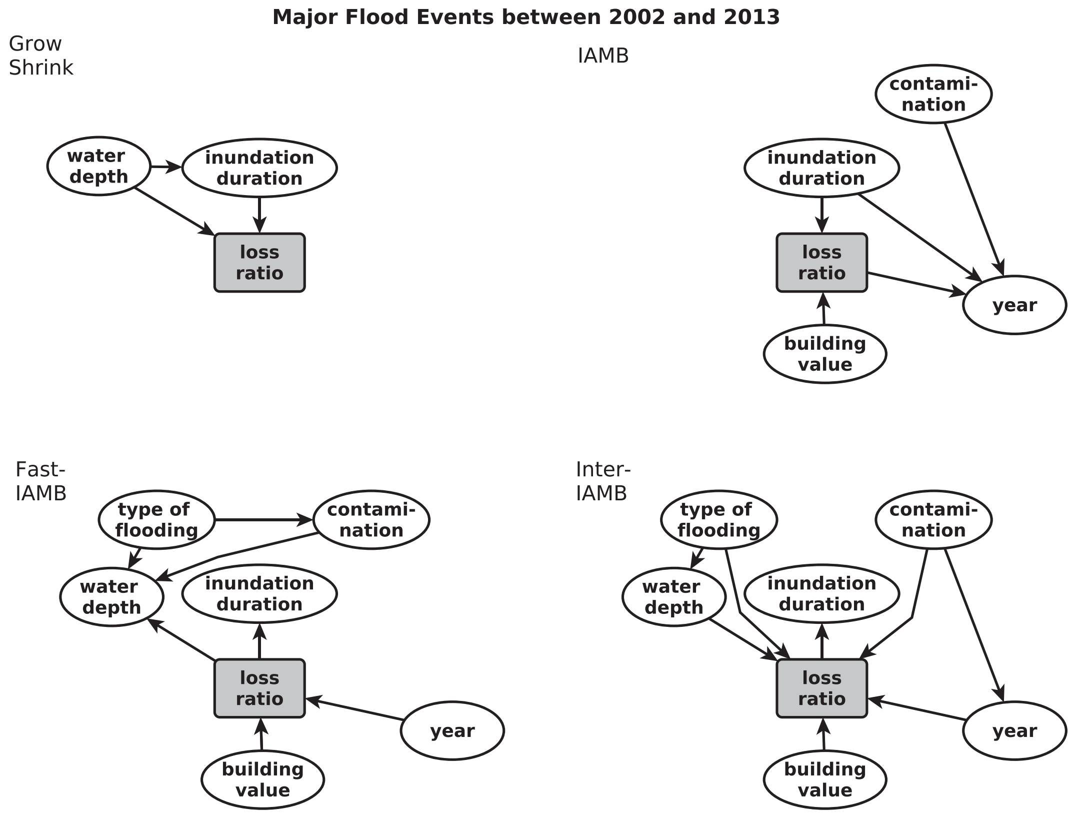

Figure 3. MB of the loss ratio based on interviews that were conducted after six major flood events between 2002 and 2013. The networks are learned with four constraint-based algorithms: GS = Grow-Shrink; IAMB = Incremental Association Markov Blanket; Fast-IAMB = Fast Incremental Association Markov Blanket; Inter-IAMB = Interleaved Incremental Association Markov Blanket.

3.2.1. Markov Blankets From All Data

Figure 3 shows the MBs of the loss ratio learned from the data set of all recorded flood events between 2002 and 2013. The four constraint-based algorithms result in different amounts of variables that build the MB of the loss ratio. The MB based on the GS algorithm consists of two variables, the MB based on the IAMB algorithm is composed of four variables and the MBs learned with the Fast-IAMB and Inter-IAMB algorithms each include six variables.

It is striking that the MBs are dominated by variables that characterize the hydrological load: inundation duration is the most common variable in all four MBs; it is followed by water depth and contamination of the floodwater that are included in three cases. Finally, the flood type is included in two MBs. Considering the variables that describe resistance characteristics, only the building value appears in the MBs; it is included in three of the four cases. The newly introduced variable year of the event is also included in three variants. The PCA already revealed that the year is related to variables on preparedness and warning, that is, refers to the flood management.

In general, the MBs are in good agreement with the PCA that attributed the highest importance for the loss ratio to the flood type, water depth, duration, and contamination, which are followed by items on the building characteristics and preparedness.

3.2.2. Markov Blankets for Different Flood Events

A distinction between the single flood events indicates differences in the damaging process of the individual events. Figure 4 shows the MBs of the building's loss ratio for the six different flood events. It is noticeable that the data from the flood of 2002 create the most complex MB with three to five variables that are linked to the loss ratio. Besides the federal state, the MB of the 2002 event contains only items that describe the kind and intensity of the flooding process: flood type, water depth, duration, and flow velocity that are interlinked. The MBs of the other events contain less predictors and only one (or even no) variable that describes the intensity

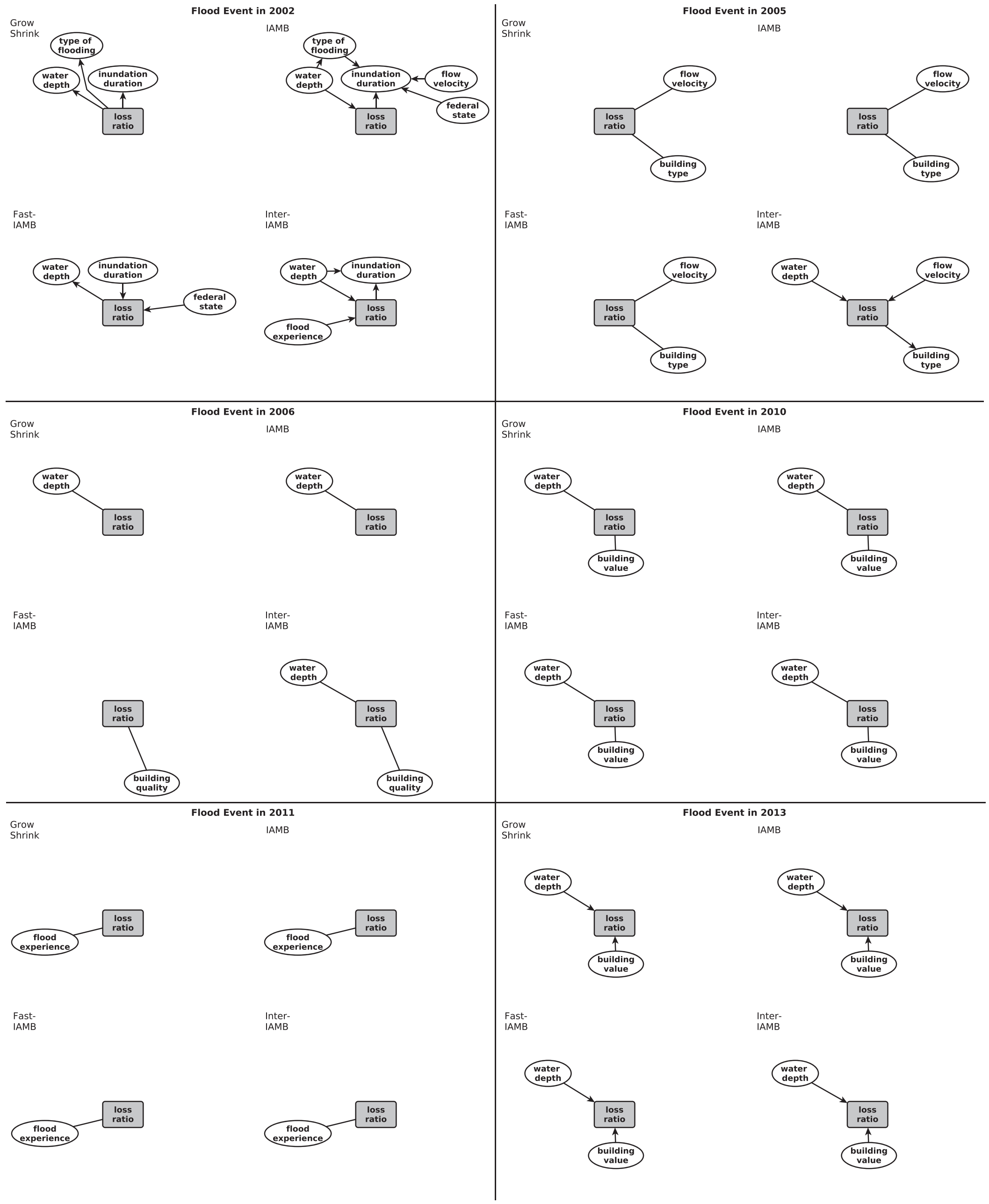

Figure 4. Markov Blankets of the flood loss ratio learned with four different constraint-based algorithms, based on data subsets that each describe one of six major flood events between 2002 and 2013 in Germany. The learned models consist of directed and undirected edges. While the directed edges clearly define the parent set of a variable, the undirected edges represent the possible orientations in both directions.

of the flood process: the water depth in 2006, 2010, and 2013 as well as the flow velocity in 2005. In 2011, flood experience is the only variable that governs the target variable flood loss ratio. While the water depth is the dominating flood variable, there are different variables that describe the building characteristics: building type (2005), building quality (2006), and value of the building (2010 and 2013) are parts of the MBs in Figure 4.

3.2.3. Markov Blankets for Different Flood Types

So far, loss models for inland water floods have been distinguished from loss models for coastal flooding (Penning-Rowsell et al., 2005). A better differentiation of models for inland water floods, considering different flood types seems to be appropriate. We take a closer look at the damaging factors for different flood types

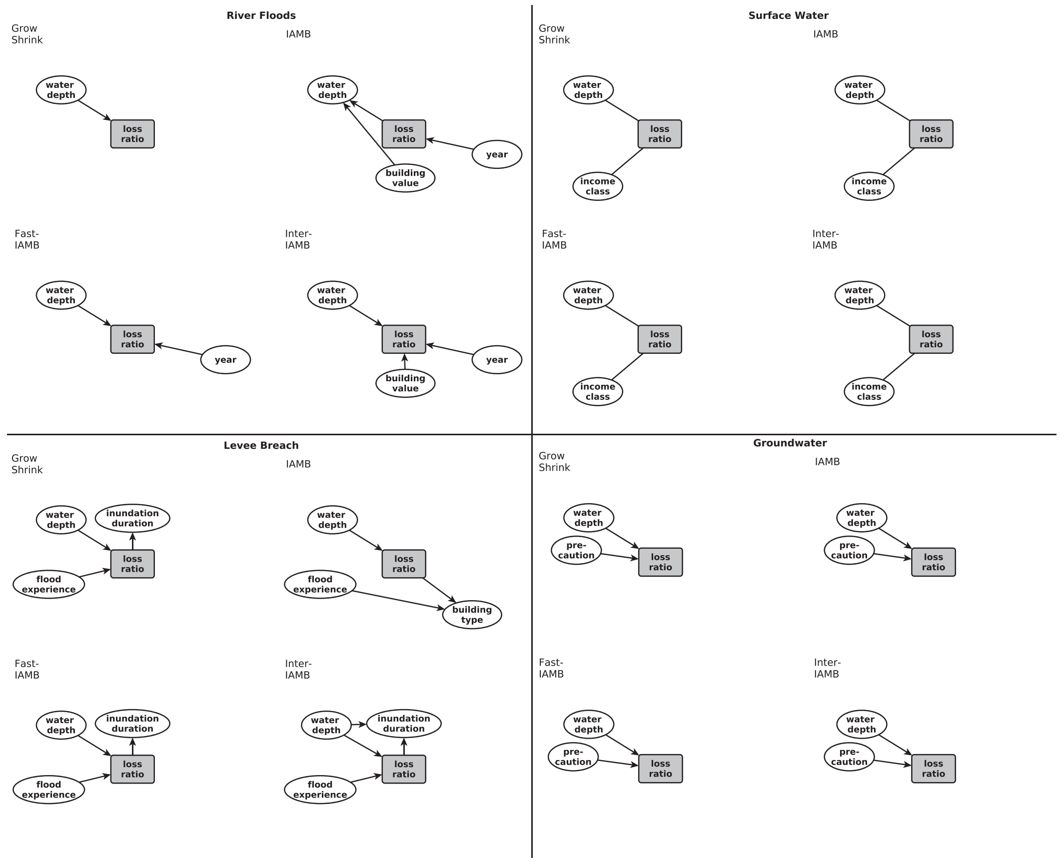

Figure 5. Markov Blankets of the flood loss ratio learned with four different constraint-based algorithms, based on data subsets that describe different types of flooding: riverine floods (1,192 records), surface water flooding (250 records), levee breaches (516 records), and groundwater floods (308 records).

by deriving individual models for the four flood types: riverine floods, surface water flooding, floods caused by levee breaches, and groundwater floods, as shown in Figure 5.

When deriving MBs for the different flood types, the water depth is again an important variable for all flood types confirming the great importance it has in flood loss modeling (Gerl et al., 2016; Merz et al., 2010). However, it is not the only damage predictor. In the MBs derived for different flood types it is usually accompanied by one or two additional predictor variables that differ for the individual flood types.

Table 6 provides all variables that are contained in the MBs of the derived models and summarizes the results. We like to stress that the provided sum of MB occurrences strongly depends on the considered data subsets, and some variables are not considered for all MB constructions. Thus, the sum does not provide an objective importance measure but rather serves as rough indicator for the relevance of the selected features.

4. Discussion

The interpretation of the networks has to be done carefully. For BNs and MBs the direction of the edges does not necessarily reflect causality, since this cannot be derived from the data. For instance, in the learned BN (Figure 2) contamination and water depth are linked by an edge, but the data do not tell whether contamination is affected by water depth or vice versa. The direction of the edges is determined according to the type of the encoded conditional (in-)dependences (see also section 2.4) and further influenced by regularization criteria, which allow only for a limited model complexity and consequently a limited number of parents per node. On top, artifacts or noise in the data may distort the result as well as hidden (and consequently not considered) impact factors.

Table 6
Variables and Their Frequency of Detection in the MB of Loss Ratio by Applying Different MB Detection Algorithms and Different Data Subsets

Algorithm	BN based	MB	MBs for different flood events						MBs for different flood types				
Data set	all data	all data	2002	2005	2006	2010	2011	2013	River	Surface	Levee	Ground	
Data set size	2283	2283	947	127	61	242	103	803	1192	250	516	308	Sum
Water depth	1	3/4	4/4	1/4	3/4	4/4		4/4	4/4	4/4	4/4	4/4	9.75
Inundation duration		4/4	4/4								3/4		2.75
Flow velocity	1		1/4	4/4									2.25
Contamination	1	3/4											1.75
Type of flooding	1	2/4	2/4						not considered				2
Federal state			2/4										0.5
Year	1	3/4	not considered						3/4				2.5
Lead time	1												1
Lead time elapsed	1												1
Precaution	1											4/4	2
Efficiency of precaution	1												1
Flood experience			1/4				4/4				4/4		2.25
Insurance	1												1
Building type				4/4							1/4		1.25
Ownership	1												1
Building quality	1				2/4								1.5
Building value	1	3/4				4/4		4/4	2/4				4.25
Income										4/4			1
(Avg.) MB size	13	4.5	3.5	2.25	1.25	2	1	2	2.25	2	3	2	

4.1. Comparison of Bayesian Network and Markov Blankets

For a comparison of the BN learned in section 3.1 with the MBs learned in section 3.2, Figure 2 highlights the variables that are included in the various learned MBs. For a better distinction, in the following we refer to the MB that is subset of the BN learned in section 3.1 as the *BN-based MB*. Its elements are shaded in gray in Figure 2. Further, the MBs that were directly learned with constraint-based algorithms in section 3.2 are denoted as *contraint-based MBs*. In Figure 2 its elements are marked by a bold frame, if they are contained in a constraint-based MB that was learned from the entire data set, or by a bold dashed frame, if contained only in at least one constraint-based MB learned from a data subset.

All variables that describe the flooding situation are detected by at least one of the learned MBs. Several of them (water depth, contamination, type of flooding, and flow velocity) even belong to both, the BN-based MB and the constraint-based MBs. This indicates high predictive power of those variables, since they are selected as relevant predictor variables by both considered model approaches.

All constraint-based MBs include less elements (maximum six variables) than the BN-based MB (13 variables). The difference is mainly due to the settings of the algorithms' control parameters, which determine the threshold for adding or removing an edge when learning BNs or MBs. Further variations result from the different procedures of both types of algorithms as well as differing discretizations of the variables. Thus, a fine discretization usually results in a less dense network structure than a coarse discretization. Despite these dis-tinctions, there is a strong overlap of the constraint-based MBs with the BN-based MB. Five out of the six variables that are included in the constraint-based MBs learned from all data, are also included in the BN-based MB: water depth, contamination, year, type of flooding, and building value. Only the inundation duration is included in the constraint-based MB, but not in the BN-based MB. This might be an effect of its strong correlation to the type of flooding, which in the BN links inundation duration to the loss ratio and might thus shield a direct effect of inundation duration on the loss ratio (Figure 2). In general, the variables identified by the BNs and the MBs are also in good agreement with the results of the PCA.

Further, variables of the BN-based MB occur as well in constraint-based MBs learned from data subsets: flow velocity, building quality, and precaution. Yet other variables are members in the BN-based MB only

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Table 7
Predictor Variables Used in Previous Flood Damage Studies

Model	FLEMOps	Regression tree		Bagging	BN	BN	BN expert[a]	BN expert[a]	BN	BN
		25 leaves	8 leaves	decision tree	MAP score	MAP score	28 nodes	10 nodes	BDE score	BDE score
Training data	Germany	Germany	Germany	Germany	Germany	Germany (Elbe)	Germany (Elbe)	Germany (Elbe)	Germany	Dutch (Meuse)
	2002	2002-2006	2002-2006	2002-2006	2002-2006	2002	2002	2002	2002-2013	1993
	$n = 1,697$	$n = 1,103$	$n = 1,103$	$n = 1,103$	$n = 1,135$	$n = 426$	$n = 426$	$n = 426$	$n = 1,456$	$n = 4,398$
Reference	(Thieken et al. 2008) (Elmer et al. 2010)	(Merz et al. 2010)			(Vogel et al. 2013)		(Schröter et al. 2014)		(Wagenaar et al. 2014)	
	model version	No of decision nodes		Ranking			included in MB			
Water depth	FLEMOps	5	3	1	x	x	x	x	x	x
Inundation duration		3		6	x	x	x	x		
Flow velocity		1		8	x	x	x			
Contamination	FLEMOps+	2		5	x	x	x	x		
Return period	FLEMOps+r	2	1	3			x	x	x	
Lead time					x		x			
Warning quality					x					
Emergency measures					x		x			
Precaution	FLEMOps+	3		7	x	x	x	x	x	
Efficiency of precaution		1			x	x				
Flood experience					x					
Knowledge of hazard					x					
Building type	FLEMOps	1					x	x		
Building quality	FLEMOps				x		x	x		
Building value		1		4			x	x		
Floor space		3	2	2						
Income		1	1				x			
Status		1					x			
Household size							x			x

[a]The BN structure is derived from expert knowledge with a causal mapping approach.

(ownership structure, insurance, efficiency of precaution, lead time elapsed without precaution, and early warning lead time) or only in constraint-based MBs learned from data subsets (flood experience, federal state, building type, and income class). The first case might be explained by the mentioned setting of the control parameters, that leads to smaller constraint-based MBs compared to the larger BN-based MB. The second case might be an effect of individual characteristics of the considered flood events/types. Yet besides the variable income class, all constraint-based MB members are either part of the BN-based MB or directly linked to one of its members and vice versa. Consequently, the detected MBs are in good agreement with each other.

4.2. Interpretation in Context With Previous Flood Damage Studies

Unsurprisingly, water depth is the most frequently detected predictor variable in our study (Table 6). It is often accompanied by a building describing feature and sometimes by additional flooding characteristics. Further, the warning situation, flood experience, or precautionary measures are in some cases considered to be relevant for the damage prediction. Those results are in good agreement with existing flood damage studies. Table 7 summarizes the results from selected flood damage studies (Elmer et al., 2010; Merz et al., 2013; Schröter et al., 2014; Thieken et al., 2005, 2008; Vogel et al., 2013; Wagenaar et al., 2018) and lists the variables that are—according to these studies—most relevant for the damage prediction. Similar to our findings, flooding characteristics, in particular, water depth, are expected to be most important, followed by building characteristics and variables related to precaution. The same order of importance appears from the PCA (see supporting information). In the following we discuss the derived graphical models in more detail.

4.2.1. Bayesian Network

Considering the BN in Figure 2 a large number of connections between the variables in the DAG are in line with expert knowledge. Accordingly, the variables describing the buildings' characteristics show an intuitive pattern of interrelations with direct links from building value to the floor space of building and the number of flats. Also the link between the number of flats and the building type is obvious. These information are typically used in flood damage functions in terms of so-called secondary damage modifiers for the differentiation of loss patterns (Gerl et al., 2016). The factors belonging to the socioeconomic status form a closely related group in the network structure with the household size in the center and thus providing context to the number of children, the number of elderly persons, the income class, and the socioeconomic status. Likewise, the warning-related factors cluster in the DAG with warning information and early warning depending on the lead time and on the warning source. This seems plausible, because the warning information and the lead time of an official warning will differ from those provided, for example, by a neighbor. This is also in line with the PCA, which identified two components with sociodemographic items and one component, which is dominated by warning variables. None of these components, however, showed a high or significant correlation with the flood loss ratio. In the BN these items are also far away from the target variable, the loss ratio.

Many of the links in the BN have also been identified as significantly correlated in the study of Merz et al. (2013), which is based on the recorded flood events in 2002, 2005, and 2006. Yet the MB of the learned BN does only partly match with the variables selected by the regression trees and bagging decision trees in Merz et al. (2013). Considering the regression tree with eight leaves, water depth is the only decision node that is included in the BN-based MB. However, two of the other three variables that form decision nodes, namely, floor space and income, are according to Merz et al. (2013) closely correlated to building value, ownership, and building quality, which in turn are included in the BN-based MB. The remaining decision node, return period, has not been considered in the current study, due to limited data availability. The larger regression tree with 25 leaves contains additional decision nodes that are part of the BN-based MB, namely, flow velocity, contamination, precaution, perceived efficiency of precaution, and building value. Again, the decision nodes which are not part of the BN-based MB (inundation duration, building type and socioeconomic status) might be explained by correlated variables that are included in the MB instead (type of flooding, ownership and building quality). This is similar for the bagging decision trees, which are used by Merz et al. (2013) to calculate the variable importance of the predictors. The variables with highest determined importance are water depth, floor space, return period, building value, contamination, inundation duration, precaution, and flow velocity in the given order. Three out of the eight variables are not part of the BN-based MB (floor space, return period, and inundation duration). As already argued these variables are either not considered in the current study or, according to Merz et al. (2013), significantly correlated to variables included in the BN-based MB.

Most of the variables used in the FLEMOps model or its extension FLEMOps+ and FLEMOps+r (Elmer et al., 2010; Thieken et al., 2008) have also been included in the BN-based MB (water depth, contamination, precaution, and building quality). Again, the return period, which was added to the model in FLEMOps+r, was not considered in the current study. The building type, which is already included in FLEMOps, is significantly correlated to building value and ownership (Merz et al., 2013), which are part of the BN-based MB.

In comparison with the expert-based BN derived from 28 variables with a causal mapping approach in Schröter et al. (2014), the currently learned BN includes comparable patterns of variable grouping and direct links between factors, even though the expert BN clearly includes more interconnections. Still the variables in the MBs of both BNs do only partly match, including water depth, contamination, flow velocity, building value, and building quality. There is also good agreement with the BNs derived from similar data sets, which comprise the flood events between 2002 and 2006 (Vogel et al., 2013) or 2002 only (Schröter et al., 2014). The corresponding MBs overlap with the newly derived MB in water depth, contamination, flow velocity, precaution, and perceived efficiency of precaution for both BNs and additionally in lead time and building quality for the BN derived from the larger data set in Vogel et al. (2013). In contrast, the MB of the BN derived by Wagenaar et al. (2018) is much smaller. This BN has been derived in a hybrid approach, that is, data driven — considering all six recorded flood events between 2002 and 2013 — and including expert knowledge on relationships between variables. The differences in the model complexity may result from the different proceeding in the model development, which was guided also by potential availability of variables for model applications in large regions. Further, the reduced data set in Wagenaar et al. (2018), which contains only complete data records, as well as differences in the variable discretization, which is equifrequent in Wagenaar et al. (2018), have an effect on the model complexity. The derived MB includes only the variables water depth, return period, and precaution. While return period is not considered in the current study, the other two variables are detected by the BN-based MB of this study. The MB in the BN that was derived by Wagenaar et al. (2018) from the larger, but more homogeneous Dutch data set even includes only two variables, from which only the water depth matches with the variables detected in the BN of this study.

There are also links in the newly learned BN which are unexpected given previous experiences and outcomes of analyses. For instance, lead time elapsed without emergency measures has not been identified as being causally linked to the loss ratio (Schröter et al., 2014) or being strongly correlated to the loss ratio (Merz et al., 2013). With regard to the newly considered factor insurance, the DAG also shows a link to precaution which points to the connection that flood insurance policies are often connected to the implementation of property-level mitigation measures. This is in line with the findings by Thieken (2018) that insured residents implement more precautionary measures than the uninsured.

4.2.2. Markov Blankets From All Data

The constraint-based MBs learned from the entire data set are dominated by variables that describe the flooding process. While the water depth is the most commonly considered variable in flood loss models (Merz et al., 2010), inundation duration is only included in few models as, for instance, the multicolored manual (Penning-Rowsell et al., 2005). Yet in the study by Merz et al. (2013) inundation duration was also used for decision nodes in the regression tree with 25 leaves, and it was among the eight variables with the highest importance factor derived with bagging decision trees. Further, the BNs learned from data subsets by Vogel et al. (2013) and Schröter et al. (2014) or derived based on expert knowledge (Schröter et al., 2014) include inundation duration in the MB of the loss ratio. The same holds for the contamination of the floodwater, which is additionally considered in the flood loss estimation model FLEMOps (Thieken et al., 2008).

The fact that the building value plays an important role in the MBs in Figure 3 is in contrast to the assumption of loss model development which assumes that by using the building's loss ratio, most of the influence of the building value is leveled out. Commonly in loss models, the size or the type of the building is considered instead, for example, by means of different building types, the floor space or the number of flats per building. Yet previous studies (e.g., Merz et al., 2013) already indicate a relevance of building value. This might be explained by the fact that building value comprises information about size, type, and quality of the building and may consequently serve as better predictor than the single other building characteristics. Another explanation could be the increased building values in recent years, for example, due to the installation of solar panels that are not affected by flooding at all. Other components such as insulation material might introduce a different vulnerability to flood water than traditional materials. Since empirical evidence is currently lacking, this topic needs further research.

The presence of the variables year and type of flooding in the MBs hints at different underlying conditions and processes for the different flood events and flood types, which are discussed in more detail in the following subsections.

4.2.3. Markov Blankets for Different Flood Events

The MBs that are derived for the single flood events differ not only in their complexity but also in the variables that are included. Except for the flood event in 2013, the differences in complexity can be explained by the amount of available data (see Table 2), since the size of the data set influences the amount of detected edges. Usually, the more data are available, the more connections can be learned. However, the sample size cannot explain the different complexity of the MBs of the flood events in 2002 and 2013, because both data sets contain almost the same amount of data. A further explanation is the mixed and heterogeneous flood situation that occurred in the three federal states that were surveyed after 2002: Bavaria, Saxony, and Saxony-Anhalt were affected to a very different extent in 2002. While 75% of the overall damage of the 2002 -flood was allocated to Saxony, that is, EUR 8.7 billion, the flood was not that exceptional in Saxony-Anhalt (EUR 1.2 billion) and Bavaria (EUR 198 million). In 2013, by contrast, these three federal states reported comparatively similar amounts of damage (Thieken, Bessel, et al., 2016).

Different from the other five events, the 2002 event was characterized by a mixture of flood types. The event started with record-breaking rainfall in the Saxon middle hills (e.g., the Ore Mountains/Erzgebirge) that triggered flash floods and surface water flooding. This was followed by high riverine floods, particularly along the rivers Mulde and Elbe, where more than 100 levees breached and inundated the hinterland. Finally, exceptionally high groundwater levels were observed, for example, in Dresden, the capital of Saxony (Kreibich & Thieken, 2009). Such heterogeneity of flood processes was not reported for the other five events, although in 2013 some major levee breaches occurred as well (Merz et al., 2014, Thieken, Bessel, et al., 2016). The more homogeneous character of the flooding might explain, in addition to the smaller amount of data, why the MBs of the other events contain less predictors and only one (or even no) variable that describes the intensity of the flood process: the water depth in 2006, 2010, and 2013 as well as the flow velocity in 2005. Like in 2002, the flood of 2005 was accompanied by many flash flood processes in the Alps.

While the water depth is the dominating flood variable, there are different variables that describe the building characteristics: building type (2005), building quality (2006) as well as value of the building (2010 and 2013) are parts of the MBs in Figure 4. In 2010 and 2013, the subsets contain data from several federal states with different socioeconomic conditions. Thus, the building value might be more informative for these events. Another issue is that in recent years the building value is much influenced and has increased, for example, by decentralized solar panels (see above). That might be a reason why the building value is becoming more important. The great influence of building characteristics on flood damage underpins that the spatial transferability of flood loss models must be done with care, since building types and construction material are often typically regional features.

In 2011, flood experience is the only variable that governs the target variable flood loss ratio. At first glance this result comes as a surprise. It indicates, that for the 2011 event the flood experience has a higher predictive power on the loss ratio than the water depth. Indeed, it can be explained by the fact that this flood hit regions with a high level of risk awareness, preparedness, and the widespread existence of property-level mitigation measures, particularly the Rhine catchment (Bubeck & Kreibich, 2011). Accordingly, the subcontracted pollster reported that many residents did not participate in the survey, because they had no financial damage owing to their good state of precaution and preparedness. For this flood event, Kienzler et al. (2015) reported the lowest average building loss and the highest level of awareness and preparedness. Consequently, flood experience may indeed serve as a predictor for losses related to the 2011 event. Moreover, the MB is based on a very small data set, which contains only 103 observations. Thus, existing dependency relations, such as between water depth and loss ratio, can be easily distorted by coincidence.

4.2.4. Markov Blankets for Different Flood Types

The differentiation of fluvial and pluvial floods in flood loss model development has recently received increasing attention, because pluvial floods have caused tremendous damage in recent years (e.g., in the city of Münster in July 2014; Spekkers et al., 2017, or the town Braunsbach in May 2016; Laudan et al., 2017) and are expected to be of increasing relevance (Malitz et al., 2011; Rözer et al., 2016). A separate consideration of the different flood types may help to address their specific characteristics. Thus, the distinct analysis of the four flood types: riverine floods, surface water flooding, levee breaches, and ground water floods, reveals differ-

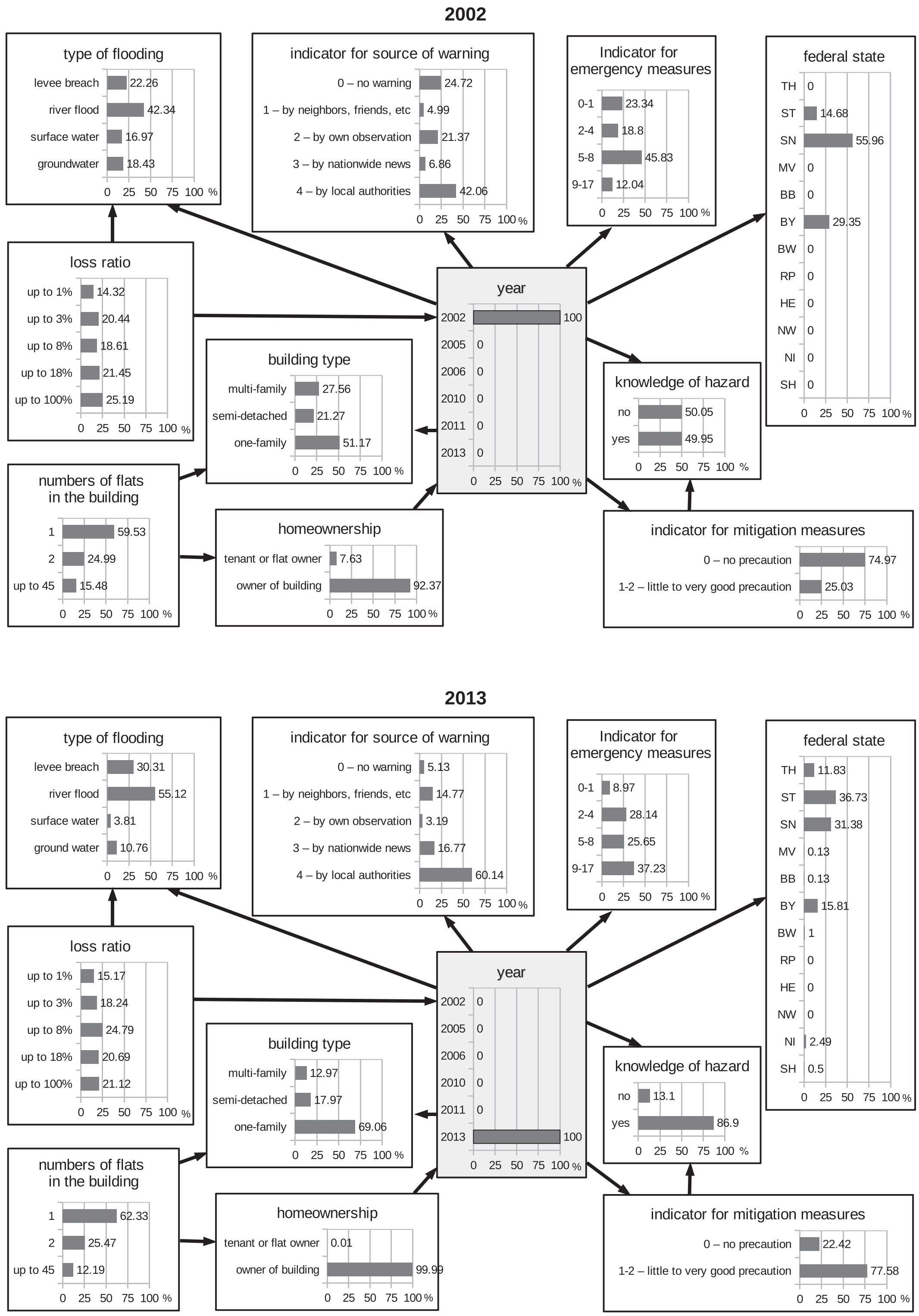

Figure 6. To illustrate the variation of prevailing circumstances over different years that is captured by the BN in Figure 2, we compare two different settings of year: year = 2002 (top) and year = 2013 (bottom). For better visualization only the subnetwork of the BN that corresponds to the MB of year is plotted. For each variable in the MB its local probability distribution, conditioned on year = 2002 or year = 2013, respectively, is provided as bar chart, reflecting the prevailing circumstances in the corresponding years. Especially the conditional distributions for knowledge of hazard and precaution indicator change significantly. The probability of knowing about the hazard increases from 50% in 2002 to 87% in 2013, and the probability of implementing any precautionary measures increases from 25% in 2002 to 78% in 2013. BN = Bayesian Network; MB = Markov Blanket.

ences in the flooding processes (Figure 5). While the water depth is again the dominating variable in the MBs detected for all different flood types, there are differences in the selection of additional predictor variables.

With regard to riverine flood, the year of the flood event is linked to the loss ratio. This indicates different dynamics of the six events as already outlined in the previous subsection (see also Table 1). It might also be an effect of the changing classification of the type riverine flood, which from 2005 on was assigned to most cases in which mixed flooding processes were reported, as mentioned in section 2.2. This method should be revised to avoid inconsistent flood type assignments.

With respect to levee breaches, the results of the MBs meet the expectation: besides the water depth, flood duration (and flood experience) plays an important role for the resulting loss. In areas affected by levee breaches the water often stays for several weeks aggravating the resulting damage due to enhanced penetration of water and contaminants. Flood experience might have an influence, because people that already experienced a previous flood are better prepared for such a situation, particularly in areas that are usually protected by dikes. At least for the 2013 flood improved precautionary behavior of residents living behind dikes has been detected (DKKV- Deutsches Komitee Katastrophenvorsorge, 2015; Thieken, 2018). Quick and efficient behavior is particularly important in such cases.

The MBs for surface water flooding and groundwater flooding are based on smaller data sets (250 and 308 records, respectively), and thus are more susceptible to noise or artifacts in the data. Consequently, they might fail to detect the most relevant dependencies. Still they detect the relation between building loss and water depth. Further, the MBs for surface water flooding suggests that income reflects the value of the buildings (and its contents) and thus determines the amount of damage. The relation between income, socioeconomic status, and value of the building is supported by the PCA. Finally, impacts of groundwater floods can be mitigated by precaution, such as flood-adapted use and robust materials of lower stories, particularly the basement.

4.3. Transferability and Multivariable Flood Damage Models

Based on the implicit assumption that flood damage models are transferable in time and to similar regions, flood damage assessments often use the same model in one region for several scenarios or in large regions with only slight adjustment of the building characteristics (e.g., asset values, composition of building types). So far this procedure lacks economical alternatives, but given the differences in the models derived for the individual flood events and different types of flooding, this assumption deserves more attention.

Even though loss model validation and particularly transferability studies are rare (Gerl et al., 2016), in most cases a drop in model performance can be observed when the models are applied to contexts different from those for which they had been originally developed (Cammerer et al., 2013; Schröter et al., 2014; Thieken et al., 2008). In contrast, Wagenaar et al. (2018) show an unexpected performance increase, when transferring flood damage models, that were derived on the German data base, to the Dutch Meuse river flood in December 1993. Yet the performance increase can be explained by the missing heterogeneity in the Dutch data set, where the relative building losses hardly exceed 10%.

If we consider the BN and MB, which were learned from the entire data set, the direct link between year and loss ratio and between flood type and loss ratio, hint at changing conditions and variations in damage processes between the different flood events and different flood types. Thus, the variable year reflects, for example, changes in the flood management (preparedness, warning, and insurance coverage; Thieken, 2018). Also, the variation of the MBs for different flood scenarios shows that the damage to residential buildings is controlled by different damaging processes. Further, the large number of variables that is directly linked with the variable year in the BN indicates a large variability in the documented conditions over the years, that is, changes in the type of flooding, preparedness (precaution, knowledge of hazard, warning source, and emergency measures), and exposure (building type and federal state). This is illustrated in Figure 6, where we consider how the probability distributions of these variables change for different states of year, comparing 2002 with 2013. Especially, the conditional distributions for knowledge of hazard and precaution indicator change significantly expressing the strong increase in knowledge of hazard and implementation of precautionary measures from 2002 to 2013. Also a shift in the distribution of warning source toward official authorities can be observed from 2002 to 2013. This reflects the considerable increase in private precaution as well as the improvement of warning systems after the 2002 flood (Kreibich et al., 2017; Thieken, Kienzler, et al., 2016).

The direct link between year and loss ratio in the BN and some MBs may also account for changing conditions, that are not captured by the considered variables, as, for example, demand surge, that is, increasing prices for construction and repair work due to shortcoming in capacities. There is anecdotal evidence for such shortcomings as reported in the media after the 2002 and the 2013 flood. The effect on the amount of reported losses is, however, unknown. A comparison of the single-event data sets further reveals that the losses from severe flood events are better documented, for example, the item-nonresponse values are lower for larger events or events with governmental disaster assistance (Thieken et al., 2017).

The large variation in the flooding and damaging processes for the individual flood events and types of flooding shows the need to allow users to take the specifics of the respective flood events into account. This makes the use of multivariable models inevitable. As already pointed out by Schröter et al. (2014) and Wagenaar et al. (2018) multivariable flood loss models may alleviate the decrease in performance of transfered models. Yet complex models, which have a high degree of freedom, require very large data sets for parameter fitting. Otherwise they will perform poorly in generalization tasks due to overfitting. It is reasonable that the limited transferability of so far-developed multivariable flood damage models, as stated by Schröter et al. (2014), results from a limited model flexibility or data limitation, or both. For a continuous improvement of transferable flood damage models it is therefore important to constantly increase the available databases. As stated by Wagenaar et al. (2018), not only the size of the data set but especially a large heterogeneity of the captured cases is important for the development of data-driven multivariable models. Further, it is essential to better understand which factors should be considered to explain temporal and spatial changes in the underlying system and which thus have to be adjusted to the region under study. The set of variables that is taken into account should be under regular critical review to ensure that it includes all relevant variables that affect the flood loss ratio. Since BNs can be learned based on data, without prior knowledge about the existing relations between the variables, they can be used to corroborate or disprove hypotheses or to reveal hitherto unknown (in-)dependencies, as, for example, the detected relation between insurance and flood loss ratio (Figure 2). Some of the variations in the damaging process might be due to hidden (so far not considered) variables, for example, demand surge.

In consideration of the high effort that is entailed in the flood damage data acquisition, it is important to make use of all information available. As mentioned in section 2.2 our data set contains several incomplete records, for example, interviewees might not want to respond to certain questions (e.g., about their economic situation) or lack some information. Still they provide important information, for example, about the flooding situation, which should be used to improve the damage prediction. Most state-of-the-art methods simply remove incomplete records from the considered data. Thus, for the PCA (see supporting information) only 526 to 1,244 out of 2,283 cases remain, if incomplete records are neglected. In contrast, graphical models do not only enable predictions based on incomplete observations but also allow us to consider incomplete observations in the process of model development (see sections 2.3 and 2.4). They consequently increase the amount of information that is included in the model construction. A comparison with the BN learned by Wagenaar et al. (2018) on a similar data base, but with incomplete data records removed, shows a significant decrease in model complexity (see Table 7). Yet this might be also due to differences in the model construction.

5. Conclusions

The application of multivariable models is inevitable, if flood damage models are aimed to be transferable across events and regions (Merz et al., 2010; Schröter et al., 2014; Wagenaar et al., 2018). This study aims to contribute a meaningful selection of predictors to be included in multivariable flood damage models. Two types of graphical model approaches, BNs and MBs, are applied to different flood events and types of flooding in order to identify the variables that are most relevant for the damage prediction. The challenge is to select a set of variables that, on the one hand, keeps the model complexity small and, on the other hand, allows a model transfer in space and time and consequently provides the flexibility to capture changing conditions. So far, the transferability of flood damage models is hardly investigated even though reliable damage models are of great importance for loss estimation and risk assessment, as for instance required by the insurance industry and strategic planners in flood risk management.

The networks, that were learned in this study, show that variables describing the hydrological load, building characteristics and precautionary measures influence the extent of damage (Table 6). These results are in agreement with previous studies on flood-damaging processes (Table 7) and the PCA (see supporting information). Based on the BN and MB that were derived from the entire data set (Figure 2) the severity of building loss is controlled by variables that describe the flood event as well as the building value. Further, according to the BN additional building characteristics as well as the precautionary measures and the timing of emergency measures are directly linked to the loss ratio. The connections of the loss ratio to the event year and flood type point to diversities in the damaging processes of the different events and indicate the need to take event specifics into account and to update loss models over time.

The consideration of the MBs for single flood events (Figure 4) reveals different impact factors for different events. The 2002 data create the most complex MBs. This event was, in contrast to the other flood events, a mixture of all considered flood types. In 2002, the loss ratio is mainly characterized by flood parameters. These seem to be especially important in the damage prediction for heterogeneous flood events. In contrast, in 2005, 2006, 2010, and 2013 the damage is, in addition to the water depth, influenced by variables that characterize the affected buildings. Building characteristics are reasonable to have a stronger impact in more homogeneous flooding situations. For 2011, the flood experience is the only detected variable which is linked to the loss ratio. This variable seems to be especially informative in high-risk zones, where large differences in the level of flood risk awareness and preparatory behavior can be observed.

The event year, which is part of MBs for riverine floods, again reflects different damaging processes of the single events, but also changes in flood risk management, particularly warning and preparedness. In general the MBs derived for different types of flooding (Figure 5) suggest that different models for different flood types are advantageous to quantify and predict damage caused by different flood types. For floods that occurred due to levee breaches, the observed loss is influenced by the water depth, flood duration, and flood experience. The consideration of these variables is plausible, since the water remains for several weeks in the affected areas, which aggravated the building damage. Further, people with flood experience are usually better prepared to flood events and may react faster and more efficient. The MBs for surface water flooding and groundwater flooding are based on smaller data sets and are consequently more susceptible to noise or artifacts in the data. Owing to the small number of cases, particularly, surface water flooding needs more attention in future research. Still the detected links from building loss to water depth and income class or precaution, respectively, can be explained by known relations.

Due to the large complexity of flood-damaging processes, further research on model calibration and validation with a particular focus on model transfer as well as on flood-damaging processes for different flood types is needed. The data collection for flood damage models is cumbersome, since there are no possibilities for a fully automatic data acquisition. Most of the data are taken by surveying affected people (see section 2.2). Particular care is required not only during the data collection but also in the process of designing the questionnaire, that is, the choice of the variables and indicators that should be derived from the data, the way how particular questions are phrased, and the options that are provided as possible answers. Identifying the relevant predictor variables can help to decrease the number of required questions and consequently increase the number of people that are willing to participate and complete the questionnaire.

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